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A Modular Multi-Agent Architecture for Hybrid Educational Recommendation Systems Integrating RAG and LLMs

Anas EL Moustamid[1], Jaber EL Bouhdidi[2]
[1]*SIGL Laboratory, National School of Applied Sciences, University Abdelmalek Essaadi, Morocco*
[2] *SIGL Laboratory, National School of Applied Sciences, University Abdelmalek Essaadi, Morocco*

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ABSTRACT

Secondary education faces persistent challenges—including heterogeneous learning styles, uneven academic levels, overloaded curricula, and declining student motivation—that hinder scalable personalization. To address these complexities, we designed a modular recommendation system based on a multi-agent architecture, where specialized AI agents collaborate to deliver adaptive learning experiences.

At the core of this system is a personalized learning assistant agent, powered by large language models (LLMs) and a Retrieval-Augmented Generation (RAG) framework. This agent dynamically analyzes student behavior, academic progress, and engagement patterns to recommend tailored content and exercises. It leverages a hybrid recommendation strategy, combining collaborative filtering (based on shared learning trajectories) with content-based filtering (factoring in subject matter, difficulty, and resource type).

Complementing this, a profiling agent continuously updates student profiles—both implicitly through interaction tracking and explicitly via input data—while a clustering agent forms student groups based on learning styles, proficiency levels, and knowledge gaps. These clusters guide the recommendation flow and allow educators to contribute curated resources aligned with each group.

A retrieval agent ensures access to relevant educational materials, while a generation agent produces semantically rich suggestions in real time, thanks to the LLM-RAG integration. The classification engine employs k-Nearest Neighbors (KNN) with Euclidean distance for matching, and Stochastic Gradient Descent (SGD) to optimize prediction accuracy.

Keywords: Recommender system, Collaborative filtering, Content-based filtering, Hybrid Approach, SGD, AI Agent, LLM, RAG.

INTRODUCTION

Secondary education faces a series of structural challenges that hinder the implementation of personalized and effective learning. One of the most striking issues is the wide disparity in skill levels among students (Sirangi 2025). In mathematics, for example, some struggle to grasp fundamental concepts like fractions or percentages, while others are ready to tackle advanced topics such as solving equations (e.g., solving 2x+5=152x+5=15) or complex geometric proofs. In French, gaps appear in grammar (e.g., distinguishing between “à” and “a”), spelling (e.g., avoiding errors like “sa va” instead of “ça va”), as well as in writing skills, ranging from simple sentences to structured and well-argued texts.

At the same time, students’ declining interest in academic content has become a major obstacle. Many question the relevance of what they are taught (e.g., “What’s the point of algebra?”), and digital distractions—social media, online games—further demotivate them, reducing their attention span. This disengagement can lead to classroom disruptions and harm the collective learning environment.

Overcrowded classrooms, rigid curricula, and a lack of tailored educational resources further complicate teachers’ tasks, forcing them to juggle remediation and enrichment without differentiated support.

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Personalized learning is changing education. It shows big results for students. Teachers say it boosts student interest and grades by a lot (Effectiveness of Personalized Learning: Statistics on Outcomes in Diverse Educational Settings 2024).

Recommendation systems are computer applications whose role is to assist users in making decisions that meet their needs (Sikka, Dhankhar, and Rana 2012). The e-learning field uses recommendation systems to tailor training to the learner's profile (Sikka et al. 2012). Recommender systems can have positive effects on learning, such as learning performance and motivation (Souabi et al. 2021).

Several technological initiatives have attempted to address these challenges. Among the most widespread are platforms like Khan Academy and Coursera, which offer structured, progressive content adapted to different learning levels. Other solutions, such as adaptive systems like Smart Sparrow or ALEKS, dynamically adjust exercise difficulty based on student responses. Collaborative environments like Google Classroom streamline course management and communication between teachers and learners, while analytics tools like Classcraft or Edmodo Insights track engagement and performance.

However, despite their added value, these technologies have limitations. Their personalization is typically restricted to difficulty adjustments, without truly accounting for cognitive style or semantic context. Moreover, the recommendations they generate remain static, based on predefined rules or raw scores, limiting adaptability. The interaction between educational resources, student profiles, and teachers remains underdeveloped, hindering the creation of more personalized learning scenarios. Finally, content classification often relies on fixed, superficial metadata without deeper evaluation of contextual relevance or alignment with specific learning objectives.

To overcome these limitations, we have designed an intelligent recommendation system structured as a multi-agent architecture (Bouhdidi et al. 2010; Jaber et al. 2016), powered by AI agents (Piccialli et al. 2025; Xing et al. 2024; Zhu et al. 2024), LLMs (Ali 2025; Piccialli et al. 2025; Sirangi 2025; Xing et al. 2024; Zhu et al. 2024), and a RAG (Dahal et al. 2025). Each agent within the system is assigned a specialized role—profiling, retrieval, generation, filtering, or coordination—allowing for distributed reasoning and modular scalability. The agents collaborate to generate real-time, contextualized recommendations based on students' academic levels, knowledge gaps, preferences, and behavioral patterns. The system adopts a hybrid recommendation strategy (collaborative filtering + content-based), enhanced by dynamic classification of teacher-curated educational resources, which are automatically enriched and indexed. The underlying modeling leverages k-Nearest Neighbors (K=15) and Stochastic Gradient Descent (SGD) to optimize matching and prediction. The results achieved (95% precision/recall, RMSE = 0.05) underscore the transformative potential of this multi-agent approach for personalized learning in secondary education.

OBJECTIVES

This paper introduces the architecture of a hybrid educational recommendation system, building upon collaborative filtering approaches (Sunita and Lobo, 2012; Koffi et al., 2021; Herath and Jayarathne, 2018) and content-based techniques (Koffi et al., 2021; Herath and Jayarathne, 2018). enriched by a modular approach based on intelligent agents. This multi-agent architecture allows dynamic personalization and functional distribution of educational tasks, ensuring fine adaptability to the needs of learners. The system integrates five main agents:

- **Interface Agent:** Interacts with learners via natural language messaging platforms (e.g. WhatsApp), detects educational intentions and updates profiles in real time.
- **LLM Agent:** Uses a Large Language Model (LLM) to produce personalized explanations, quizzes and feedback adapted to the cognitive profile and academic background of each learner.
- **RAG Agent:** Integrated into a RAG (Retrieval-Augmented Generation) pipeline, it semantically retrieves relevant educational resources from a vectorized knowledge base.
- **Recommendation Agent:** Combines the results of collaborative filtering and content-based filtering to suggest optimal learning paths, targeted resources, and peer-to-peer interactions.
- **Coordinating Agent:** Oversees the entire system by ensuring task delegation, profile synchronization and semantic consistency between agents.

Journal of Information Systems Engineering and Management
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The system aims to:

- Personalize learning paths by analyzing student performance, preferences, and learning styles to recommend tailored resources.
- Enable real-time monitoring for teachers to identify struggling students and adapt instructional strategies accordingly.
- Predict and improve student performance through adaptive feedback and targeted interventions.
- Enhance student engagement and motivation by delivering context-aware, interactive, and relevant content.

This paper is structured as follows: Section 2 reviews the state of the art, Section 3 describes the system architecture, Section 4 methodology, Section 5 presents results, section 6 discusses the experimental results, and Section 7 concludes the study while outlining future research directions.

RELATED WORKS

In (Bouhdidi et al. 2010) the authers proposed an innovative architecture based on the coupling of multi-ontologies and multi-agent systems to automatically generate personalized learning paths. Their model is grounded in goal-oriented pedagogy, structured according to Bloom's taxonomy, and enables software agents to collaborate with human agents (learners, teachers, instructional designers) to dynamically construct educational sequences tailored to individual profiles. The architecture incorporates six specialized agents (interface, manager, content builder, test builder, filter, and profile manager) that communicate using standard agent languages (KQML, FIPA-ACL) to coordinate the retrieval, composition, and evaluation of educational resources. This approach allows for fine-grained adaptation to user preferences, learning levels, and cognitive styles, while ensuring the reusability of educational services. The work stands as a foundational reference in the domain of multi-agent systems for education, establishing the basis for distributed and semantically coherent personalization of learning pathways.

In (Sikka et al. 2012), the authors proposed the use of web mining techniques to develop an agent capable of recommending online learning activities or shortcuts on a course website, based on learners' access history. The aim is to enhance navigation through course materials and support the online learning process. These techniques fall under integrated web mining, as opposed to offline web mining used by experts to identify online access patterns.

In (Sunita and Lobo 2012) the authors proposed a course recommendation system architecture based on the analysis of student preferences. The system aims to suggest subject combinations that align with learners' interests. However, their approach lacks empirical validation and quantitative results, which limits the assessment of its effectiveness. Moreover, several crucial technical aspects are not addressed, such as data quality, biases in student choices, or the handling of incomplete data.

(Jaber et al. 2016) proposed an adaptive e-learning architecture based on the competencies-based approach, combining semantic ontologies with a cooperative multi-agent system. The model is structured into four pedagogical layers (interface, filtering, description, physical), each managed by specialized agents responsible for communication, personalized learning path generation, and resource management. Five ontologies (competencies, resources, training, process, actors) enable fine-grained modeling of learner profiles, educational content, and instructional objectives. Ten intelligent agents collaborate to dynamically construct customized learning paths, generate assessments, adapt resources to individual learning styles, and provide tutoring and remediation. This approach allows for granular adaptation to learners' individual needs while ensuring interoperability, reusability of resources, and functional scalability through the modularity of the multi-agent system.

In this paper (Kolekar, Pai, and M 2017), the authors proposed to identify learners' learning styles by capturing their learning behaviors in the e-learning portal using Web Log Mining. The learning styles are then mapped to the categories of the Felder-Silverman Learning Style Model (FSLSM). The authors use the Fuzzy C Means (FCM) algorithm to cluster the collected behavioral data into FSLSM categories. They employ a Backpropagation Neural Network enhanced by the Gravitational Search Algorithm (GSBPNN) to predict learning styles in real time.

In (Herath and Jayarathne 2018) the authors proposed an intelligent recommendation system for e-learning structured into three modules: a learner module, a domain module, and a recommendation module. The system recommends resources based on students' activities, performance, and preferences, using both collaborative and content-based filtering. It employs data mining techniques (clustering, classification, regression) to refine recommendations, but the system lacks innovation compared to recent approaches.

In (Koffi et al. 2021) The authors developed a hybrid algorithm that uses Convolutional Neural Networks (CNNs) to predict student performance and recommend courses. This model outperformed the k-NN approach with higher accuracy (97.31%), recall (99.98%), and a lower mean squared error (0.0251). However, the validity of the results is limited by unaddressed data biases and a very small test sample (nine learners), which compromises the generalization of the conclusions.

In (Alshaikh et al. 2021) the authors used a recommendation system (RS) based on collaborative filtering to optimize the choice of specialization after the preparatory year. To develop this system, they applied Pearson correlation to measure student similarity and the k-NN (k-nearest neighbors) algorithm to predict the most suitable specialization. The system's effectiveness is validated by an accuracy of 70.83%, as well as a 10-fold cross-validation, which improved accuracy to 74.79%. However, the absence of a student feedback mechanism prevents the system from dynamically adjusting based on user responses and progress

(Koosha, Ghorbani, and Nikfetrat 2022) This research introduced a new two-step recommendation system, utilizing demographic data and user ratings from the public Movie Lens dataset. In the first step, clustering is applied to the demographic data to group users into homogeneous clusters by combining the Firefly Algorithm (FA) and K-means. The inclusion of FA helps avoid local optima, a major limitation of K-means, thereby enhancing performance. In the second step, two recommendation systems are implemented for each cluster: one based on K-Nearest Neighbor (KNN) and the other on Naïve Bayes classification. The results, evaluated using internal and external measures such as the Davies-Bouldin index, precision, accuracy, recall, and F-measure, demonstrate that the K-means/FA/KNN approach outperforms existing models in terms of effectiveness.

In (Dahal et al. 2025) the authors proposed an extension of Moodle into a Learning Experience Platform (LXP) that integrates AI-based recommendation systems. Its goal is to personalize learning in higher education using various types of recommendations: content-based, collaborative, session-driven, trending, and learner-rated. To enrich this experience, the system leverages Large Language Models (LLMs) and Retrieval-Augmented Generation (RAG), enabling a chatbot within Moodle to provide relevant, contextual responses to students' questions. The architecture includes an external recommendation server, specialized Moodle plug-ins, a semantic search vector database, and an LLM proxy. Techniques used include TF-IDF and cosine similarity for resource matching, Graph Neural Networks for session-based recommendations, and Z-score analysis to detect popular resources. Preliminary evaluation with computer science students showed strong engagement with external resources and a positive reception to recommendations, despite limited participation in rating activities. The system—named "Learning with AI"—combines personalization, accessibility, and ethical awareness of AI to enhance the learning experience.

In (Piccialli et al. 2025) the authors presented a comprehensive review of large language model-based multi-agent systems (LLM-MAS), structuring the analysis around five fundamental modules: agent profile creation, environment perception, autonomous actions (including memory, reasoning, and planning), agent interactions, and evolution mechanisms. These systems exploit the advanced capabilities of LLMs to simulate social environments and solve complex tasks, with diverse applications in software development, robotics, scientific experiments, games, societal simulation, economics, recommendation systems, and disease propagation.

Our research is grounded in a thorough analysis of existing recommendation systems, leveraging their strengths while addressing their limitations. We rely on proven techniques—such as collaborative filtering, content-based filtering, and the integration of learner preferences—to ensure personalized and relevant recommendations. However, our approach introduces key innovations through the integration of an autonomous Agent AI, capable of dynamically modeling learning behaviors and guiding recommendations. This agent is powered by a Large Language Model (LLM), which enables deep understanding of user intent and natural interactions. To further enhance contextual relevance, we incorporate a Retrieval-Augmented Generation (RAG) architecture, which enriches recommendations by retrieving relevant educational content from external knowledge bases. Together, these components improve prediction accuracy, adapt content to various learning styles and proficiency levels, and adjust

Journal of Information Systems Engineering and Management
2025, 10(58s)
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https://www.jisem-journal.com/

Research Article

recommendations in real time through continuous feedback loops. As a result, our system aims to deliver a robust and adaptive solution, suited to the challenges of complex educational environments and optimized for an individualized learning experience.

ARCHITECTURE

To meet the requirements for large-scale personalization in secondary education, we designed a distributed architecture based on a cooperative multi-agent system, where each agent plays a specialized role in the educational recommendation cycle. This approach enhances the system's modularity, scalability, and contextual responsiveness.

Our architecture relies on five core agents, interconnected through an asynchronous communication layer. Each agent operates autonomously in its functions but remains coordinated to ensure dynamic adaptation to student profiles. The figure below (Figure 1) illustrates the interactions between the agents.

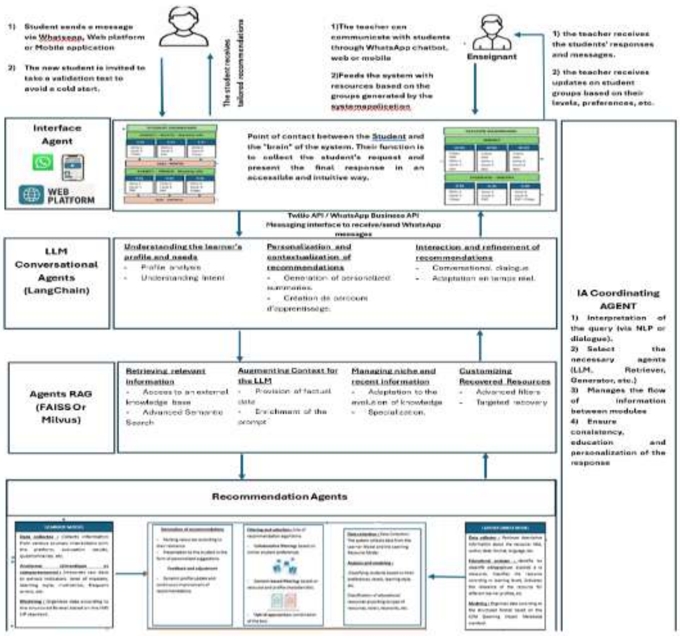

Figure 1 : The proposed Multi-Agents architecture of our system

Agent Interface

The Agent Interface is the system's entry point for users (students and teachers). It manages:

- The collection of interaction data (Quiz, time spent, exercise responses).
- The explicit entry of preferences or learning objectives.

The transmission of requests to internal agents. It also ensures integration with external platforms (e.g., WhatsApp via Twilio) for real-time notifications and feedback.

LLM Agent

The LLM Agent is responsible for the semantic generation of recommendations. Based on a Large Language Model, it:

- Reformulates teaching suggestions in language appropriate to the student's level.
- Generate personalized explanations, summaries, or questions.
- Interacts with the RAG Agent to enrich responses with relevant content. Its role is crucial for contextualizing recommendations and improving cognitive engagement.

RAG Agent

The RAG (Retrieval-Augmented Generation) Agent combines retrieval and generation capabilities:

Journal of Information Systems Engineering and Management
2025, 10(58s)
e-ISSN: 2468-4376
https://www.jisem-journal.com/
Research Article

- It queries educational resource databases indexed via FAISS or Milvus.
- It selects the most relevant documents according to the student's profile.
- He transmits these documents to the LLM Agent for contextualized reformulation. This coupling makes it possible to produce recommendations that are both informed and adapted to the learning context.

Recommendation Agent

The educational resource recommendation system plays a central role in personalizing learning by delivering content tailored to each student's level, needs, and preferences. At its core, the system relies on two foundational components Learner Model and Learning Object Model:

- **Learner Model**

The learner model is a central concept in adaptive educational systems and personalized learning environments (Herath and Jayarathne, 2018). It represents a modeling of a learner's knowledge, skills, preferences, and behaviors, allowing for tracking progress and adapting pedagogical content to specific needs (Herath and Jayarathne, 2018; Sani, Mohammadian, and Hoseini, 2012). Based on data collected during interactions, the learner model evolves dynamically to provide an optimized learning path. Several standards have been developed to ensure the interoperability, consistency, and quality of learner models, the most popular being IMS LIP (Learner Information Package), which is used in our approach.

A well-constructed learner profile enables the personalization of the learning experience by taking into account the learner's characteristics, preferences, skills, and behaviors (Ikram et al. 2021). In our approach, each learner accessing the system for the first time is invited to complete an initial assessment aimed at gathering key information about their knowledge, learning preferences, and skills. In the absence of historical data, these learners face the cold start problem, which reduces the accuracy of initial recommendations. This evaluation helps overcome the issue by establishing a foundation for personalization from the outset, thereby avoiding irrelevant suggestions that could negatively affect motivation. Over time, the learner's profile is enriched through interactions with the system, enabling progressively refined recommendations and a more effectively tailored learning experience.

- **Learning Object Model**

The Learning Resource Model (LRM) is a detailed framework designed to describe and classify each educational content available on a learning platform according to recognized standards. It defines the intrinsic characteristics of resources by incorporating descriptive metadata such as title, description, content type (video, quiz, PDF), author and creation date, subject, sub-subject, academic level, duration, and difficulty (beginner, intermediate, advanced), as well as the prerequisites required to ensure continuous progression.

To ensure interoperability and effective standardization of educational resources, several standards have been developed, such as SCORM (Sharable Content Object Reference Model), Dublin Core, IMS Learning Design, and IEEE Learning Object Metadata (LOM). Among these, our approach favors the IEEE LOM standard (Al-Khalifa & Davis, 2006; Manouselis, Kastrantas & Tzikopoulos, n.d.) due to its ability to finely structure the metadata of learning objects. This structuring facilitates their reuse, sharing, and adaptation within digital educational environments. The model is primarily populated by teachers through manual or semi-automated submission forms. This process contributes to optimized content management, enhancing both the quality of the learning experience and the relevance of recommendations provided to learners.

These models are represented as feature vectors: $\vec{u}$ for the learner and $\vec{r}$ for the resource. The Recommendation Agent computes a relevance score using techniques such as collaborative filtering (based on peer learning behaviors) and content-based filtering (based on resource attributes and learner preferences). Similarity measures such as cosine similarity are used to evaluate the alignment between learner needs and resource characteristics:

$$sim(u,r) = \frac{\vec{u}.\vec{r}}{\|\vec{u}\|\|\vec{r}\|} \quad (1)$$

Journal of Information Systems Engineering and Management
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https://www.jisem-journal.com/ **Research Article**

To enhance engagement and precision, K-NN classification is applied to the Learner Model to group similar profiles, enabling cluster-based personalization and targeted recommendations.

The recommendation process is orchestrated by the Intelligent Agent (IA), which coordinates the interaction between specialized agents. Upon receiving a query or detecting a pedagogical need, the IA triggers the RAG Agent, which retrieves semantically relevant educational documents from a vectorized knowledge base using tools such as FAISS, Milvus, or Weaviate. These initial results are passed to the Recommendation Agent, which applies the filtering strategies described above to select the most appropriate materials based on the Learner and Learning Object Models.

Once filtered, the refined set of resources is sent back to the RAG Agent, which leverages a Large Language Model (LLM)—such as GPT-4, Claude 3, Mistral, or Gemini 1.5 Pro—to generate personalized outputs. These include contextualized explanations, adaptive quizzes, and targeted feedback aligned with the learner's cognitive profile and current learning objectives.

This bidirectional interaction between agents ensures that recommendations are not only statistically optimized but also pedagogically meaningful, semantically coherent, and dynamically responsive to each learner's evolving journey.

Agent IA

At the heart of the architecture, the AI Agent plays the role of intelligent coordinator, ensuring synergy between the various specialized agents in the system. It orchestrates the interactions between:

- The Recommendation Agent, responsible for proposing personalized educational resources.
- The RAG Agent, responsible for contextual document retrieval via vector databases such as FAISS, Milvus or Weaviate.
- The LLM Agent, which generates adapted content (explanations, quizzes, feedback) from enriched prompts.

The AI Agent oversees the synchronization of these agents, ensuring that information flows and decisions are consistent and aligned with learning objectives. It also tracks the overall performance of the system, analyzing metrics such as precision, recall, and RMSE.

In response to user feedback and engagement metrics, it dynamically adjusts agent settings and can initiate readjustments in clusters or profiles in the event of behavioral drift or a change in objective. This central role allows the system to remain adaptive, robust and relevant in the face of diverse learning paths.

METHODS

Unlike many studies that rely on the Movie Lens dataset, which, despite being widely used, lacks diversity and fails to reflect real-world educational interactions. The problem was studied through a series of experiments on a real-world dataset representing profiles of secondary school students from a private school group and a corpus of annotated educational resources (El Moustamid and El Bouhdidi 2025). The profiles included variables such as skills, learning styles, assessment results, and explicit preferences. The resources were characterized by their subject, difficulty level, format, and learning objectives.

The evaluation focused on the system's ability to generate relevant and tailored recommendations, measuring the quality of the suggestions using standard recommendation metrics: Precision@k, Recall@k, and RMSE (Root Mean Square Error).

The experiments were conducted in a Python 3.11 environment, with the following libraries:

- **LangChain** for agent orchestration and prompt management
- **FAISS** for vector indexing and semantic search
- **Scikit-learn** for the implementation of collaborative filtering, content-based filtering, and K-NN classification
- **SentenceTransformers** for generating embeddings for profiles and resources

Journal of Information Systems Engineering and Management
2025, 10(58s)
e-ISSN: 2468-4376
https://www.jisem-journal.com/
Research Article

- **Hugging Face Transformers** for integrating LLM models (GPT-4, Mistral)
- **Milvus** for distributed vector storage and search
- **Twilio API** for communication with users via WhatsApp

The simulations were executed on a machine equipped with an Intel i7 processor, 32 GB of RAM, and an NVIDIA RTX 3080 graphics card for LLM model acceleration.

Algorithms

K-Nearest Neighbors

Classification algorithms are essential tools for categorizing learners based on their characteristics, behaviors, preferences, and performance (El Moustamid, El Mokhtar, and Bouhdidi 2017). These algorithms enable the personalization of the learning experience by identifying specific profiles and adapting educational resources accordingly (El Moustamid, El Bouhdidi 2025).

Stochastic Gradient Descent (SGD)

Stochastic Gradient Descent is an iterative optimization algorithm used to minimize a loss function, commonly employed in machine learning for training models (e.g., linear regression, neural networks). Unlike Batch Gradient Descent, which computes the gradient using the entire dataset, SGD updates parameters using a single randomly selected data point (or a small mini-batch) at each step.

In our system we used the SGD algorithm to personalize the learning, we used this algorithm to adjust course materials dynamically based on a student's progress, strengths, and weaknesses (suggest Next lessons based on past performance, Difficulty level adjustments, suggest Learning paths).

RESULTS

The experimental results underscore the effectiveness of the hybrid recommendation system tailored for secondary education. By integrating collaborative filtering with content-based techniques, and leveraging algorithms such as K-NN for learner profile clustering and SGD for prediction optimization, the system achieved impressive performance metrics: 95% accuracy, 95% recall, and a 95% F1 score on the test set. These outcomes confirm the system's capacity to deliver highly personalized educational recommendations while facilitating the discovery of new learning content in dynamic environments. A key factor contributing to this success is the incorporation of a conversational Agent AI, which enables real-time interaction with learners through intuitive platforms like WhatsApp. This agent interprets natural language queries and pedagogical intents, dynamically updates learner profiles, and orchestrates the recommendation process. As a result, it enhances both the precision of recommendations and learner engagement

Figure 2:Student home screen

Journal of Information Systems Engineering and Management
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Research Article

Figure 2: This interface is designed to visualize a student's individual progress within a predefined competency. It includes general information about the student, a comprehensive list of targeted competencies, and a progress indicator for each of them.

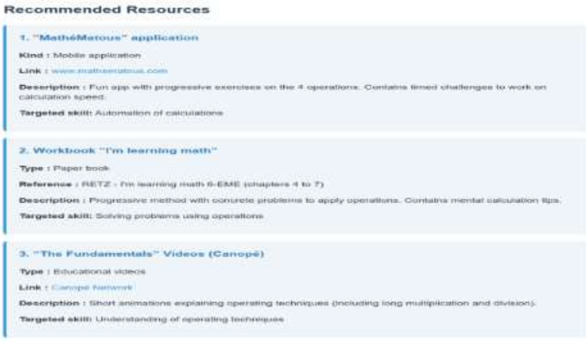

Figure 3: List of recommended resources

Figure 3 : Through this interface, students can access relevant educational resources for their chosen competency. All these resources are tailored to their profile and available in various formats (text, video, etc.).

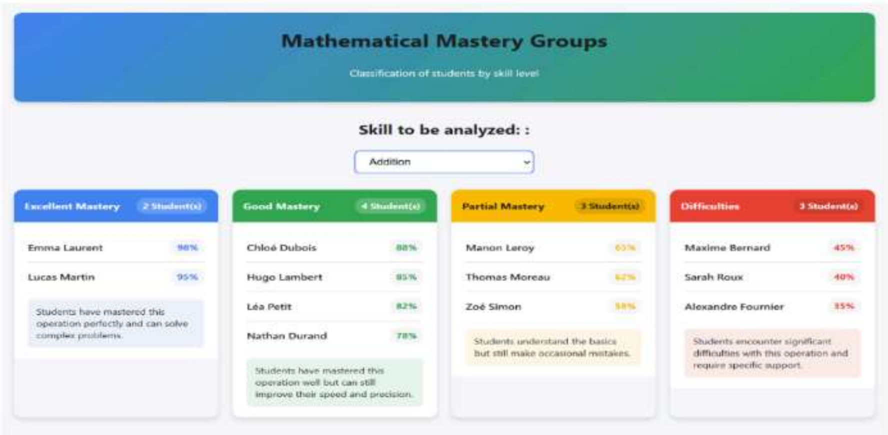

Figure 4: Teacher Dashboard

Figure 4: This interface represents a section of the teacher's dashboard, providing a global view of students' proficiency levels in a given skill. The teacher selects a skill from those taught, and the system categorizes students into groups based on their mastery level. In addition to this classification, the interface enables the teacher to suggest educational resources tailored to each student's specific needs, fostering a more personalized and effective learning experience

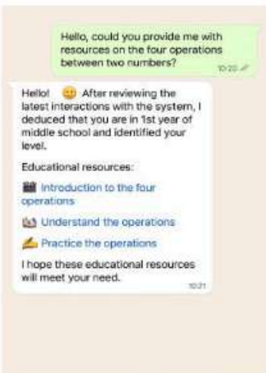

Figure 5: Interaction between a Student and the Intelligent System via WhatsApp

The Figure 5 illustrates a typical conversation between a 1st-year student and the intelligent recommendation system. The student formulates a natural language query asking for resources on the four mathematical operations. The system, after consulting the interaction history and identifying the school level, rephrases the request and suggests suitable educational resources as clickable links. This conversational interface, accessible via WhatsApp, enables intuitive and personalized interaction, which increases learner engagement and facilitates access to relevant educational content.

DISCUSSION

The results demonstrate that integrating a multi-agent architecture into an educational recommendation system significantly enhances relevance, personalization, and learner engagement. By comparing the performance of the multi-agent system—enriched with RAG pipelines and LLM models—to more traditional approaches (collaborative filtering, content-based filtering), notable improvements are observed in precision, recall, and semantic coherence.

The system's effectiveness lies in the functional specialization of its agents. The **RAG Agent** ensures fine-grained semantic retrieval of educational documents, while the **Recommendation Agent** applies hybrid filtering techniques to refine suggestions. The **LLM Agent** enriches recommendations by generating contextualized and cognitively adapted content. The **AI Agent** plays a pivotal role in orchestrating the entire process, supervising performance, and dynamically adjusting system parameters based on user feedback.

A focused study on students struggling with mathematics illustrates the system's ability to address specific learning needs. Improvements in assessment scores and high engagement rates suggest that content personalization—when guided by intelligent agents and semantic models—can have a direct impact on learner motivation and academic progress.

CONCLUSION

This work proposes an educational recommendation system based on a hybrid approach, combining collaborative filtering, content-based filtering, and semantic search. The integration of AI agents, Retrieval-Augmented Generation (RAG) pipelines, and a WhatsApp interface enables contextualized recommendations and the adaptation of resources to the specific needs of students.

The results obtained confirm the relevance of the hybrid approach in enhancing the quality of recommendations while promoting learner engagement. This system contributes to more equitable education by addressing disparities in access to educational content.

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